SINGLE CHANNEL ANALYSIS OF ELECTROMAGNETIC BRAIN SIGNALS THROUGH ICA IN A DYNAMICAL SYSTEMS FRAMEWORK

C. J. James and D. Lowe
Neural Computing Research Group, Aston University, Birmingham, United Kingdom

Abstract- **This paper introduces a method for extracting information from single channel recordings of electromagnetic (EM) brain signals. In a dynamical embedding framework, the measured electroencephalogram (EEG) and magnetoencephalogram (MEG) signals are assumed generated by the non-linear interaction of a few degrees of freedom. In a three-step process, first an appropriate embedding matrix is constructed out of a series of delay vectors from the measured signal. Then independent component analysis (ICA) is performed on the embedding matrix to decompose the single channel recording into its underlying independent components (ICs). The ICs are treated as a convenient expansion basis and subjective methods are then used to identify components of interest relevant to the application. These ICs are then projected back onto the measurement space in isolation. The method has been applied to single channels of both EEG and MEG recordings and is shown to isolate, amongst others: i) artifactual components such as ocular, electrocardiographic and electrode artifact, ii) seizure components in epileptic EEG recordings and iii) theta band, tumour related, activity in MEG recordings.**

Keywords **– EEG, MEG, ICA, dynamical embedding, single channel analysis**

I. INTRODUCTION

The analysis of the time varying electromagnetic (EM) fields of the brain provides a valuable insight into the functioning of the human brain. Signals of interest range from observations of seizure activity in ictal electroencephalographic (EEG) recordings, to evoked visual fields in magnetoencephalographic (MEG) recordings of normal subjects. It is generally desirable to observe signals of specific morphology and/or occupying particular frequency bands. This goal is rarely achievable directly from naïve recordings of EEG and MEG data, for the most part this is due to the large amount of artifact that contaminate the ongoing brain activity of interest.

When only a single channel of recording is available, or when the signal of interest is only present in one or very few channels of a multi-channel recording, the difficulty of isolating signals of interest is increased. Many methods attempt to isolate such activity, using mimetic methods or broadband filtering methods to remove (or at least attenuate) those undesirable components in the recordings. Here we introduce a method whereby it is possible to break down single channel recordings of the EM brain signals into their underlying components, irrespective of the components' origin (physiological or otherwise). The method relies on a standard implementation of Independent Component Analysis (ICA), which has caused much interest in the biosignal analysis community recently [1],[2],[3],[4] and [5]. Most methods applying ICA to biosignal analysis rely on spatial (i.e., multichannel) analysis. The method we introduce can isolate multiple underlying components using only the temporal information inherent in the single channel recordings.

II. METHODOLOGY

We introduce a three-step process where; *A*: We first capture the temporal dynamics of the recorded data through a technique known as dynamical embedding (DE). *B:* This is followed by the standard implementation of ICA to extract multiple independent components (ICs). *C:* Subjective methods are then used to identify components of interest that are then projected back onto the measurement space in isolation.

A. Dynamical Systems Analysis

Given a sampled time series, through DE we attempt to uncover as much information as possible about the underlying generators based only on the measured data [6]. This is based on the assumption that the measured signal is due to the nonlinear interaction of just a few degrees of freedom, with additive noise, and suggests the existence of an unobservable deterministic generator of the observed data. If the number of degrees of freedom of the underlying system is given by D, then D can be used as a coarse measure of system complexity. Takens' [7] theorem allows us to reconstruct the unknown dynamical system that generated the measured time series by reconstructing a new state space based on successive observations of the time series.

A DE matrix is constructed from a series of delay vectors taken from the observed data $x(t)$, say, where the state of the unobservable system at time t, $X(t)$, is given by

$$X(t) = \{x(t-\tau), x(t-2\tau), \ldots, x(t-(m-1)\tau)\} \in \Re, \quad (1)$$

where τ is the lag and m is the number of lags or the embedding dimension. This delay vector describes observations of the underlying system states, assuming that the data, $x(t)$, $t=1,2,\ldots,N$, are generated by a finite dimensional, nonlinear system of the form

$$x(t) = f[X(t-1), X(t-2), \ldots, X(t-D)] + e_t, \quad (2)$$

where $x(t)$ is real valued, and e_t is independently and identically distributed, and zero mean with unit variance.

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
25 Oct 2001	N/A	-

Title and Subtitle Single Channel Analysis of Electromagnetic Brain Signals Through ICA in A Dynamical Systems Framework	**Contract Number**
	Grant Number
	Program Element Number
Author(s)	**Project Number**
	Task Number
	Work Unit Number
Performing Organization Name(s) and Address(es) Neural Computing Research Group Aston University Birmingham, United Kingdom	**Performing Organization Report Number**
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500	**Sponsor/Monitor's Acronym(s)**
	Sponsor/Monitor's Report Number(s)

Distribution/Availability Statement
Approved for public release, distribution unlimited

Supplementary Notes
Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom.

Abstract

Subject Terms

Report Classification unclassified	**Classification of this page** unclassified
Classification of Abstract unclassified	**Limitation of Abstract** UU

Number of Pages
4

Takens showed that the Euclidean embedding dimension $\hat{m}$ must be at least as large as D, but in practice must be such that,

$$\hat{m} > 2D + 1 . \tag{3}$$

When applied to real world data the delay vector size m actually used needs to be a lot larger than the Euclidean embedding dimension ($\hat{m}$) because of dependencies in the time series data and inherent noise in the system. m needs to be 'big enough' to capture the information content necessary and if the time series data is heavily correlated, then more time series samples are needed to make up the required information content of the delay vector. Once the optimal delay vector size is found, an embedding matrix is constructed out of a number of consecutive delay vectors. The number of delay vectors N, is determined by the length of the signal to be analysed but in practice must be at least as large as m. Hence the embedding matrix consists of a series of delay vectors such that

$$\mathbf{X} = \begin{bmatrix} x_t & x_{t+\tau} & \cdots & x_{t+N\tau} \\ x_{t+\tau} & x_{t+2\tau} & \cdots & x_{t+(N+1)\tau} \\ \vdots & \vdots & \ddots & \vdots \\ x_{t+(m-1)\tau} & x_{t+(m)\tau} & \cdots & x_{t+(m+N-1)\tau} \end{bmatrix}. \tag{4}$$

Provided the sampling rate of the acquired data is chosen sensibly, then the practical minimum size for m can be chosen based on the lowest frequency of interest and the lag τ can be set to 1, i.e.,

$$m \geq \frac{f_s}{f_L}, \ \tau = 1 , \tag{5}$$

where f_s denotes an appropriate sampling frequency, and f_L the lowest frequency of interest in the measured signal. For the EM brain signals described here, we derived values for m and τ in this manner, and over a diverse set of neurophysiological test signals, the choice of $m = 90$ and $\tau = 1$ proved optimal. If the choice of lag term τ, delay vector size m and number of lag vectors N is adequate, the embedding matrix is now rich in information about the temporal structure of the measured data. If N is set such that the embedding matrix covers a quasi-stationary signal, it becomes possible to extract an estimate for the unobserved degrees of freedom D.

We now choose to represent the data in the embedding matrix by a convenient spanning basis, in our case we choose ICA. It is in fact possible to span the embedding matrix with any basis, such as Principle Component Analysis (PCA) for example, but we have shown in previous work [2] that the use of such an orthogonal spanning set as a means of identifying underlying components in EM brain signal data yields less useful results than ICA.

B. Independent Component Analysis

ICA performs a blind separation of statistically independent sources, assuming linear mixing of the sources at the sensors, generally using techniques involving higher-order statistics. Several different implementations of ICA can be found in the literature; [1],[8],[9] and [10]. This paper is not meant as an overview of the various ICA algorithms and we will restrict ourselves to the use of the Fast ICA algorithm, [10] and [11], mainly because of its ease of implementation and speed of operation. Further details about the other algorithms can be obtained from the given references.

In essence, ICA assumes a set of k measured data points $\mathbf{v}(t) = [v_1(t), v_2(t), \ldots, v_k(t)]^T$ to be a linear combination of l unknown and statistically independent sources $\mathbf{s}(t) = [s_1, s_2, \ldots, s_l]^T$ (assuming $l \leq k$). The matrix describing the linear combination of the $\mathbf{s}(t)$ is called the mixing matrix, and is given by the full rank $k \times l$ matrix $\mathbf{A}$ such that

$$\mathbf{v}(t) = \mathbf{A}\mathbf{s}(t). \tag{6}$$

The algorithms must find a separating or de-mixing matrix $\mathbf{W}$ such that

$$\mathbf{s}(t) = \mathbf{W}\mathbf{v}(t), \tag{7}$$

given the set of observed values in $\mathbf{v}(t)$.

In Fast ICA, the ICA problem is posed as an optimisation problem with the ICs as its solution. The Kurtosis, or fourth cumulant, that is used to describe the peakedness of a distribution is defined as

$$kurt(\mathbf{v}) = E\{\mathbf{v}^4\} - 3\left(E\{\mathbf{v}^2\}\right)^2 , \tag{8}$$

for a zero-mean random variable $\mathbf{v}$. Further details about the Fast ICA algorithm can be found in [10].

ICA brings with it some restrictions, which can be summarized as, (a) neither energies nor signs of the ICs can be calculated, and (b) there is no ordering between the ICs. In our implementation of ICA for EM brain signal analysis we make assumptions that are in keeping with the general assumptions governing the application of ICA. In particular we assume that:

1. The measured EEG/MEG is a linear summation of the electrical/magnetic activity from various brain regions.
2. The EM field distribution is spatially fixed and only the electrical 'strength' is changing within these regions.
3. Any activity of interest is independent of the ongoing background EM brain activity. This certainly holds true for most artifacts and to activity such as seizure activity - at least early on in the evolution of a seizure.

Performing ICA on the embedding matrix **X** results in a set of ICs that form a basis that spans the embedding matrix. Because Fast ICA assumes a square mixing matrix (i.e., as many sources as there are sensors are assumed) there are as many ICs as measurement 'channels' – m in this case. Furthermore, as the ICs are unordered subjective means must be used to identify ICs of interest.

C. Selecting and Projecting ICs of interest

Selecting relevant ICs is not a trivial task. The nature of the square mixing matrix means that a great many more sources will be identified over the expected (smaller) number of sources underlying a measurement set. In the case of the embedding matrix of embedding dimension m=90 there will be a total of 90 ICs – whereas it will be generally assumed that the number of underlying sources *of interest* should number much less than that. Many subjective methods can be derived that can rank ICs but ultimately the relevance of each IC depends on the type of data being analysed and the purpose of the analysis (e.g., artifact removal, evoked potential/field analysis, epileptogenic source analysis, etc.).

Once a subset of p ICs ($p < m$) has been chosen the ICs must be projected back to the measurement space such that

$$\mathbf{Y}^i = \mathbf{a}_i \mathbf{s}_i^T, \tag{9}$$

where $\mathbf{s}_i$ is the i^{th} IC (i =1, 2, ..., p), $\mathbf{a}_i$ the corresponding column of the mixing matrix **A** and $\mathbf{Y}^i$ the resulting 'embedding matrix'. From $\mathbf{Y}^i$ it now becomes possible to extract the projected time series, $y_i(t)$, by performing an average of the rows of the embedding matrix $\mathbf{Y}^i$, in order to unembed the time series, i.e.,

$$y_i(t) = \frac{1}{m}\sum_{k=1}^{m} Y^i{}_{k,(t+k-1)}\,, \tag{10}$$

for t = 1, 2, ..., N, where $Y^i{}_{k,\,(t+k-1)}$ refers to the element of $\mathbf{Y}^i$ indexed by row k and column t+k-1.

III. Results

This section depicts some results obtained on applying the method to various EM brain signals acquired under different conditions, from both EEG and MEG recording modalities. It is intended as a general overview of typical results obtained when using this method over a diverse set of EM brain signal recordings.

Fig. 1. depicts a selection of ICs chosen from a single channel analysis of a 6s epoch of MEG recorded from over the right temporal lobe of a child with a known tumour in the right temporal lobe. Multichannel MEG data, sampled at 2kHz, was recorded with a CTF Systems Inc MEG

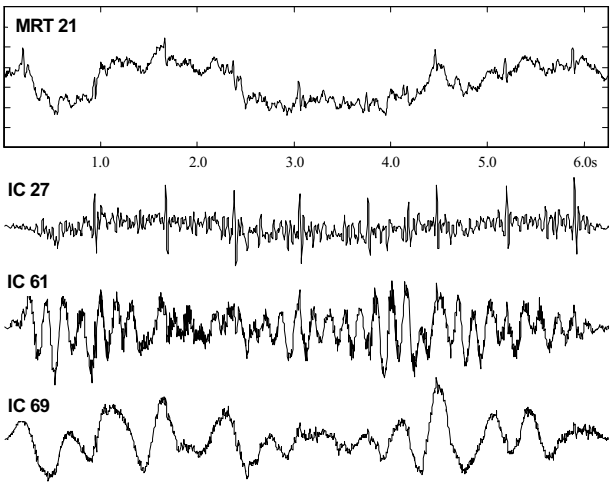

Fig. 1. A 6s segment of ongoing MEG recorded from over right temporal lobe of a child with a right temporal tumour. IC 27 depicts ECG ac tivity, IC 61 alpha band activity and IC 69 theta band activity, most probably due to the tumour.

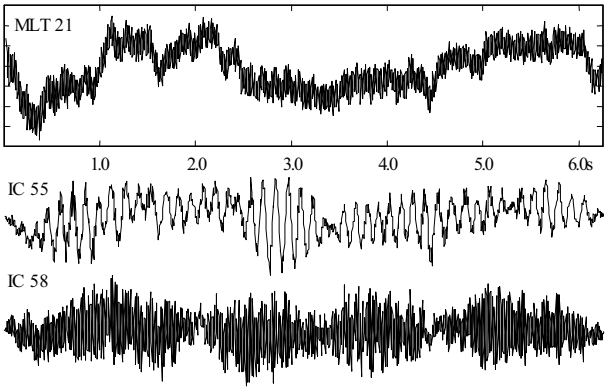

Fig. 2. A similar segment of MEG to that of Figure 1, recorded from over left temporal lobe of the same patient. IC 55 depicts alpha activity and IC 58 depicts 50Hz contamination. Theta band activity was not apparent in these ICs.

scanner. Channel MRT 21 from over the right temporal lobe was chosen to assess the capability of the method in isolating both artifacts and other signals of interest. The data was down sampled to a sampling rate of 200Hz, and a dynamical embedding matrix was constructed with $\tau = 1$, $m = 90$ and $N = 1300$ samples. Fast ICA was then applied to the embedding matrix, and each resulting IC was projected back to the measurement space in the manner described in the previous section. The choice of the most relevant ICs was based on the subjective analysis of the wave morphology and on derived spectrograms of each projected IC. In Fig. 1. IC 27 depicts ECG contamination, IC 61 depicts alpha band activity and IC 69 depicts theta band activity – which we attribute to the underlying tumour.

Fig. 2. depicts a similar analysis on the same set of recordings, this time the contralateral channel to the previous right temporal channel is analysed. This channel shows gross 50Hz contamination that is isolated in IC 58, as

well as alpha band activity given by IC 55. There does not appear to be any IC depicting theta band activity in this contralateral channel.

Fig. 3. depicts a single channel (T9) of a 20s segment of ictal EEG (average reference) showing a seizure of focal left temporal lobe onset occurring 7-8s into the segment. Initial channels involved are channels T3, T5, T9 & F9, the seizure then spreads to wider regions over the next few seconds. In previous work [12] we have performed ensemble ICA on this seizure and amongst other artifactual components, ensemble ICA isolated 3 distinct seizure related IC's – each with a slightly different topography and morphology (see [12] for further details). Fig. 3. depicts a number of ICs of interest projected back to the measurement space. IC 68, IC 82 and IC 88 each depict waveforms which we attribute to seizure components – based on their morphology, their time of onset and their spectral characteristics. The temporal distribution of the three components, as well as their morphologies, matches the three components obtained from ensemble ICA.

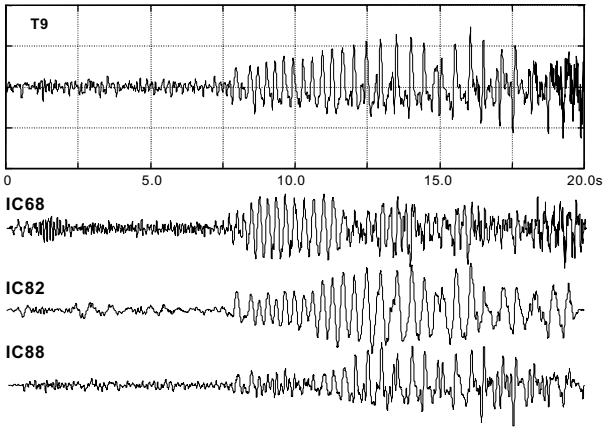

Fig. 3. Performing dynamical embedding followed by ICA on channel T9 (left temporal lobe) of a left temporal onset seizure. IC 68, IC 82 and IC 88 each depict waveforms which we attribute to seizure components. The temporal distribution of the three components as well as their morphologies matches three components obtained from ensemble ICA.

IV. Discussion

The use of a dynamical systems framework followed by ICA has been shown to yield meaningful results when applied to various sets of recorded EM brain activity. The method lends itself well to applications where multichannel recordings are not available or are undesirable. Furthermore, it is suitable in situations where multichannel recordings *are* available but where the signals of interest are limited to localised areas and/or contribute only a small percentage of the overall power of the multichannel recordings. In the latter case, it is highly unlikely that ensemble ICA on such multichannel data will successfully extract such relatively small components.

The method is particularly useful in isolating artifactual components such as ocular artifact in both EEG and MEG, or ECG artifact in MEG recordings – amongst others. When applied to epileptiform EEG data the method manages to isolate multiple seizure components underlying single channel observations of seizures. The method also identifies normal rhythms such as alpha activity, in EM brain signals, and was particularly successful in identifying slow theta activity in MEG data, most probably due to an underlying tumour.

V. Conclusion

Overall, the method is successful is isolating components from single channel data. At this stage, the choice of 'relevant' components is still highly subjective – however this is a current problem with all ICA applications to neurophysiological data and not particular to just this method. This notwithstanding, it is a very powerful method that can extract information that is not apparent in the strongly contaminated EM brain signal recordings, especially in situations where multichannel data is either unavailable or its use is undesirable.

Acknowledgment

We gratefully acknowledge funding from EPSRC grant #GR/L94673 through which this work has been made possible. We also thank the Welcome Trust Laboratory for MEG Studies of Aston University for MEG data and the Montreal Neurological Institute and Hospital for the EEG data.

References

[1] S. Makeig, T.P. Jung, A.J. Bell, D. Ghahremani, and T.J. Sejnowski, "Blind separation of auditory event-related brain responses into independent components," *Proc. Natl. Acad. Sci., USA*, 94, pp10979-10984, 1997.

[2] K. Kobayashi, C.J. James, T. Nakahori, T. Akiyama, and J. Gotman, "Isolation of epileptiform discharges from unaveraged EEG by independent component analysis," *Electroenceph. clin. Neurophysiol.*, 110, pp1755-1763, 1999.

[3] L. De Lathauwer, B. De Moor, and J. Vandewalle, "Fetal electrocardiogram extraction by blind source subspace separation," *IEEE Trans. Biomed. Eng.,* 47, 5, pp567-572, 2000.

[4] R. Vigário, J. Särelä, V. Jousmäki, M. Hämäläinen and E. Oja, "Independent Component approach to the analysis of EEG and MEG recordings," *IEEE Trans. Biomed. Eng.,* 47, 5, pp589-593, 2000.

[5] G. Wübbeler, A. Ziehe, B.-M. Mackert, K.-R. Müller, L. Trahms and G. Curio, "Independent Component Analysis of noninvasively recorded cortical magnetic DC-fields in humans," *IEEE Trans. Biomed. Eng.,* 47, 5, pp594-599, 2000.

[6] D.S. Broomhead and G.P. King, "Extracting qualitative dynamics from experimental data," *Physica*, 20(D), pp217-236, 1986.

[7] F. Takens, "*Dynamical Systems and turbulence, Lecture Notes in Mathematics,"* Springer, D.A. Rand, and L.S. Young, (Eds), 898, pp366-381, 1981.

[8] P. Comon, "Independent component analysis, a new concept?", *Signal Processing*, 36, pp287-314, 1994.

[9] A.J. Bell, and T.J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," *Neural Computation*, 7, pp129-1159, 1995.

[10] A. Hyvärinen, and E. Oja, "A fast fixed-point algorithm for independent component analysis," *Neural Computation*, 9, pp483-1492, 1997.

[11] FastICA MATLAB Package [Online]. Available: http://www.cis.hut.fi/projects/ica/fastica

[12] C.J. James, and D. Lowe, "Using Dynamical Embedding to Isolate Seizure Components in the Ictal EEG," *IEE Proc.-Sci. Meas. Technol.,* 147, 6, pp1350-2344, 2000.